

# EfficientNetB3 Architecture for Diabetic Retinopathy Assessment using Fundus Images

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**Abstract** Classification of the stages of diabetic retinopathy (DR) is considered a key step in the assessment and management of diabetic retinopathy. Due to the damage caused by high blood sugar to the retinal blood vessels, different microscopic structures can be occupied in the retinal area, such as micro-aneurysms, hard exudate and neovascularization. The convolutional neural network (CNN) based on deep learning has become a promising method for the analysis of biomedical images. In this work, representative images of diabetic retinopathy (DR) are divided into five categories according to the professional knowledge of ophthalmologists. This article focuses on the use of convolutional neural networks to classify background images of DR according to disease severity and on the application of pooling, Softmax Activation to achieve greater accuracy. The aptos2019-blindness-detection database makes it possible to verify the performance of the proposed algorithm.

**Keywords** Deep learning · Convolutional neural networks · EfficientNet · Diabetic retinopathy.

## 1 Introduction

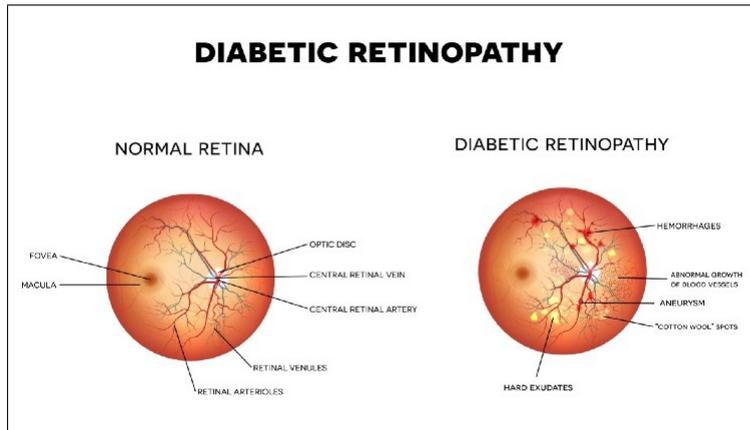
### 1.1 Diabetes

Diabetes is a complete metabolic disorder that can lead to various vascular complications in the body. In addition, when the disease coexists with other general illnesses (hypertension, obesity, high cholesterol, etc.), the risk of eye complications will also increase. Diabetes damages the small blood vessels in

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the retina, which is the back layer of the eye. This is called diabetic retinopathy. The retina converts the light and images that enter the eye into neural signals sent to the brain [1]. Diabetic retinopathy is a common complication of diabetes that affects retinal function as shown in figure 1. This pathology occurs when the blood vessels in the retina degenerate. These damaged blood vessels can dilate, causing fluid (plasma, lipid, and / or blood) to leak or even become blocked, leaving part of the retina without blood flow. All of these phenomena that occur due to diabetes can cause progressive damage to the structure of the eyeball, leading to severe vision loss or even blindness [2].



**Fig. 1** Normal retina and retina with diabetic retinopathy

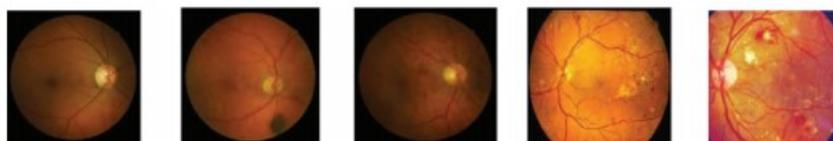
## 1.2 Phases of diabetic retinopathy

The existence and degree of the anomaly determine the severity of the disease. Identifying such manifestations as micro aneurysms, bleeding, new blood vessel formation, and venous beads is the primary diagnostic process. Micro aneurysms are blood clots 100 to 120  $\mu\text{m}$  in size, usually round in shape. Blood escaping from a ruptured blood vessel is called a hemorrhage. The abnormal growth of tiny blood vessels is called neovascularization. Venous beading refers to the expansion of the center of the vein adjacent to the occluded arteriole. Patients with diabetic retinopathy are divided into patients with diabetic non proliferative retinopathy (NPDR) and diabetic proliferative retinopathy (PDR). In addition, depending on the severity of the disease, NPDR patients can be divided into mild, moderate NPDR patients. and severe. The stages of severity of diabetic retinopathy are described in figure 2. Pictures of the various stages of diabetic retinopathy [3]. The parts of this article are classified as follows: Part 2 provides a review of the research literature. Section 3 specifies

the materials and methods proposed. Section 4 reviews the results and discussion of the proposed system and the performance evaluation. Finally, section 5 specifies the full conclusion of the document.

**Table 1** Different stages of DR.

Stages of DR	ophthalmoscope recordings	Corresponding label in the proposed algorithm
Normal	Without any abnormalities	Healthy retina
Mild NPDR	Presence of micro aneurysms only	DR stage 1
Moderate NPDR	Microaneurysms are present but in a smaller amount to severe NPDR	DR stage 1
Severe NPDR	Venous beading in two or more regions Prominent intraretinal microvascular abnormality in one or more regions	DR stage 2
PDR	. Vitreous/pre-retinal hemorrhage . Neovascularization	DR stage3



**Fig. 2** Stages of DR starting from healthy fundus image[25]

## 2 Related works

[1h] The computer-assisted detection system can accurately detect the level of diabetic retinopathy, which makes it very popular among researchers. Over the past decade, many studies have focused on the development of computer-assisted systems capable of automatically detecting diabetic retinopathy using traditional machine learning algorithms. Quellec et al. [4] used the traditional KNN algorithm and two categories of optimal filters to achieve an AUC of 0.927. In addition, Sinthanayothin et al. [5] have proposed an automated system that uses the KNN algorithm to detect the morphological features of diabetic retinopathy, and its sensitivity and specificity are 80.21% and 70.66%, respectively. In addition, in the article [6], neural networks are used to classify diabetic retinopathy into three categories. They divided mild, moderate, and severe diabetic retinopathy into accuracy rates of 82.6%, 82.6%, and 88.3%, respectively. Larson et al. [7] The automatic diagnosis of diabetic retinopathy

is shown on the background photo of the visibility threshold. They achieved 90.1% detection accuracy for real cases and 81.3% accuracy for false cases. Agurto et al. [8] used a multiscale decomposition based on amplitude modulation and frequency modulation to distinguish images of diabetic retinopathy from images of normal retina. In [9], the author reports that the area under ROC is 0.98 for the texture characteristics and an accuracy of 99.17% for the two-class classification using the wavelet transform with SVM. Jelinek et al. [10] have proposed an automated detection of diabetic retinopathy by combining the work of Spencer and the Cree system. de Spencer [11] and the Cree system [10], which achieved a specificity of 90%. and a sensitivity of 85% Abràmò et al. [12] for the automatic detection of diabetic retinopathy they created an Eye-Check algorithm. They detected anomaly lesions with an AUC of 0.839. Dupas et al. [13] have developed a computer-assisted detection system with KNN classification. Acharya et al. [14] uses the SVM classifier based on bispectrum invariant characteristics to classify the five categories. Achieve sensitivity, specificity and precision of 82%, 86% and 85.9% respectively. They also studied four characteristics and obtained a classification accuracy of 85%, a specificity of 86% and a sensitivity of 82%. Roy Chowdhury and others. [15] proposed a two-step classification method. First, it eliminates false alarms. Then use GMM, KNN, and SVM for classification tasks. They achieved a sensitivity of 100%, an AUC of 0.904 and a specificity of 53.16%. Deep learning algorithms have become popular in recent years. Kaggle [16] has initiated several competitions focused on automatic scoring for the detection of diabetic retinopathy. Pratt et al. [17] introduced a CNN-based method that has surpassed even human experts in classifying advanced diabetic retinopathy. Kori et al. [18] Use a set of connected ResNet and Densely networks to detect diabetic retinopathy and advanced stages of macular enema Torrey et al. [19] to detect lesions on retinal fundus images, they developed a more interpretable CNN model. In a similar study [20], an unbalanced weight map methodology is used by Yang et al. [21] in order to emphasize the detection of lesions with an AUC of 0.95. In [22] the VGG-16 and Inception-4 networks were used for efficient classification of diabetic retinopathy.

### 3 Materials and the proposed method

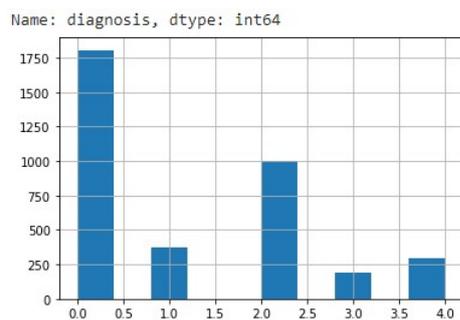
#### 3.1 Environment

The scripts are written in Python 3 on the Jupyter notebook on colab. No configuration is required and computing resources, including the GPU, are accessible free of charge.

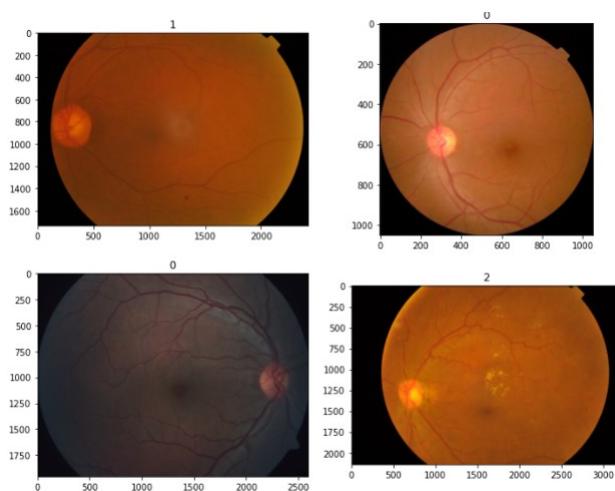
#### 3.2 Dataset

The dataset (aptos2019-blindness-detection) contains 3662 high resolution color images labeled as training set and 1928 color images that are not labeled as

training set. In each group, the images are divided into 5 groups according to the severity of the existing DR. Label 0 represents the control group. Labels 1 to 4 represent mild, moderate, severe and proliferative DR, respectively. The following is a visual summary of the diagnostic distribution as shown Figure 3. The group size is obviously unbalanced, with more than 1,800 images representing the control group (label = 0), and less than 300 images in the most severe category (label = 4). While this imbalance is expected in real world data, it poses a problem for many machine learning models. In addition to the unbalanced category, the image sizes in the dataset are also different as shown in Figure 4.



**Fig. 3** Distribution of diagnoses in the dataset



**Fig. 4** Random sample of images present in the training set

### 3.3 Method proposed

The objective of this research is to classify the fundus images with great precision in the different stages of diabetic retinopathy. classification of patients in the different stages of diabetic retinopathy in a rapid manner is necessary. Thanks to this research and to the application of an EfficientnetB3 architecture, we try to increase the accuracy of the classification in the study of images of diabetic retinopathy.

#### 3.3.1 Image preprocessing

#### 3.3.2 Resize Image

When defining the architecture of the model, which will be explained in detail in a later section, one of the requirements is to define a fixed input form. When performing this task, it is important to keep in mind that there is a balance between speed of computation and loss of information. For clarification, when the size of an image is reduced, information (pixels) is removed. Less information means faster training times; however, it can also mean reduced overall accuracy. an image size of 300 x 300 has been select-ed.

#### 3.3.3 Dataset augmentation

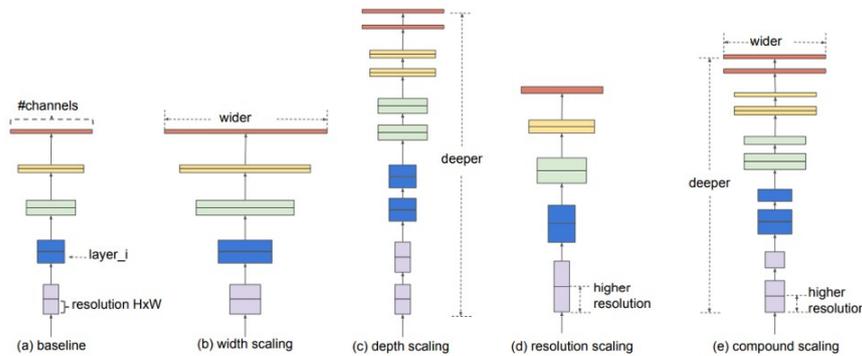
The common problem in machine learning is unbalanced group size. During the training of our models, the goal is to improve the precision during the following iterations (eras). Since the model learns by find-ing patterns to distinguish groups from one another, under-represented groups will be seen less often and therefore will not be learned as well as their over-represented counterparts. To mitigate the consequences of over / under-representation, data augmentation is used. By adjusting specific parameters, applying random changes to the original training images. These random changes are applied to each epoch, which means that the model will train on "different" images at each iteration.

#### 3.3.4 Convolutional neural network

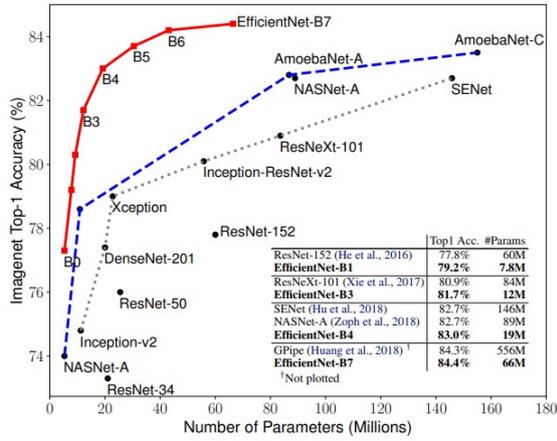
Convolutional neural network is a deep-learning neural network. It is a type of acyclic (feed-forward) artificial neural network, in which the communication pattern between neurons is inspired by the visual cortex of animals between neurons is in-spired by the visual cortex of animals. Neurons in this region of the brain are arranged so that they correspond to overlapping regions when tiling the visual field<sup>1</sup>. Their operation is inspired by biological processes<sup>2</sup>, they consist of a multilayer stack of perceptrons, the pur-<sup>3</sup>pose of which is to preprocess small amounts of information [23]. there are different CNN architectures like Lenet, Alexnet, Googlenet, ConvNet, ResNet, etc. In this research, we used the EfficienNet Architec-<sup>4</sup>ture which is introduced by Google AI.

### 3.3.5 Proposed EfficientNet architecture

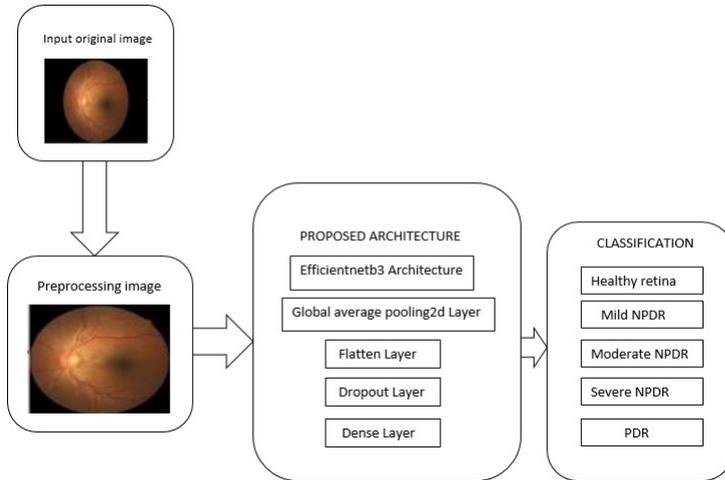
The EfficientNetB3 Convolutional Network is a network architecture where provides a new scaling method that uniformly scales all dimensions of network depth, width and resolution as shown in figure 5. This architecture applies the grid search strategy to find the relationship between the different basic network scaling dimensions under a fixed resource constraint. The could find the appropriate scaling coefficients for each of the dimensions to be scaled by applying this strategy. Using these coefficients, the basic network was scaled to the desired size [24]. By comparing EfficientNets with other existing CNNs on ImageNet. Typically, by reducing the parameter size and FLOPS by an order of magnitude, the EfficientNet model can achieve greater accuracy and efficiency than existing CNNs. For example, in high precision systems, our EfficientNet-B7 achieves a peak accuracy of 84.4% in the top 1 / 97.1% in ImageNet top 5, at the same time 8.4 times smaller than previous Gpipe, 6.1 times faster CPU inference speed. Compared to The widely used ResNet-50, EfficientNet-B4 uses similar FLOPS, and 7 improves top 1 accuracy from 76.3% of ResNet-50 to 82.6% (+ 6.3%) as shown in figure 6. Table 1 and Figure 7 illustrate the network architecture of our proposed method that can detect diabetic retinopathy by severity classification. The resolution of the network input layer is 300 x 300 pixels. We extend the architecture of EfficientNet by adding GlobalAveragePooling2D, Flatten and Dropout by 0.5 to reduce overfitting and Soft-Max layer with five classes. The architecture is optimized for 3662 sample images in 40 epochs, the learning rate is 0.00005 and the Adam optimizer is used for faster network optimization. Table 2 provides a summary of our training hyper parameter settings



**Fig. 5** Model Scaling. (a) is a baseline network example; (b)-(d) are conventional scaling that only increases one dimension of network width, depth, or resolution. (e) is our proposed compound scaling method that uniformly scales all three dimensions with a fixed ratio [24]



**Fig. 6** Model Size vs. Accuracy Comparison. EfficientNet-B0 is the baseline network developed by AutoML MNAS, while Efficient-B1 to B7 are obtained by scaling up the baseline network. In particular, our EfficientNet-B7 achieves new state-of-the-art 84.4% top-1 / 97.1% top-5 accuracy, while being 8.4x smaller than the best exist-ing CNN [24]



**Fig. 7** Flow diagram of the proposed method

## 4 EXPERIMENTAL RESULTS

In this article, we have proposed a classified model by implementing the deep learning approach; exact-ly, we built a model based on the EfficientNetB3 architecture and an aptos2019-blindness-detection dataset to train and test it. In figure7. below, the screenshot shows part of the experimental results obtained and fig. show the details of the accuracy obtained and the loss error. The accuracy of the pro-posed model is 98.26%.

**Table 2** Modified EfficientNetB3 architecture for classification of diabetic retinopathy images

Layer (type)	Output shape	Parameter
Efficientnetb3(Functional)	(None,10,10,1536)	10783535
Global average pooling2d 5(Pooling)	(None, 1536)	0
Flatten-5 (Flatten)	(None, 1536)	0
Dropout-5 (Dropout)	(None, 1536)	0
Dense-4 (Dense)	(None, 5)	7685

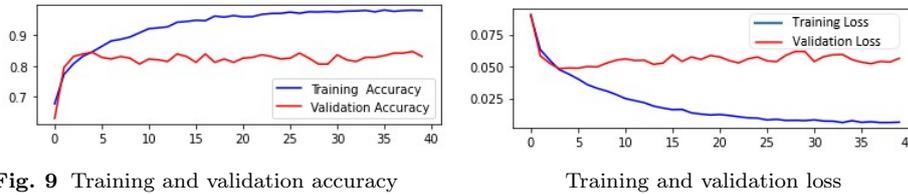
**Table 3** The summary of the settings of our training hyper parameters.

Hyper parameters	Values
Loss Function	MSE
Optimizer	Adam
Batch Size	32
Epoch	40

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Epoch 37/40
102/102 [=====] - 119s 1s/step - loss: 0.0063 - accuracy: 0.9776
Epoch 38/40
102/102 [=====] - 119s 1s/step - loss: 0.0056 - accuracy: 0.9808
Epoch 39/40
102/102 [=====] - 119s 1s/step - loss: 0.0057 - accuracy: 0.9814
Epoch 40/40
102/102 [=====] - 119s 1s/step - loss: 0.0057 - accuracy: 0.9826

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**Fig. 8** This screenshot represents a part of the training process of our proposed model**Fig. 9** Training and validation accuracy

Training and validation loss

#### 4.1 Performance Evaluation on Severity Grading

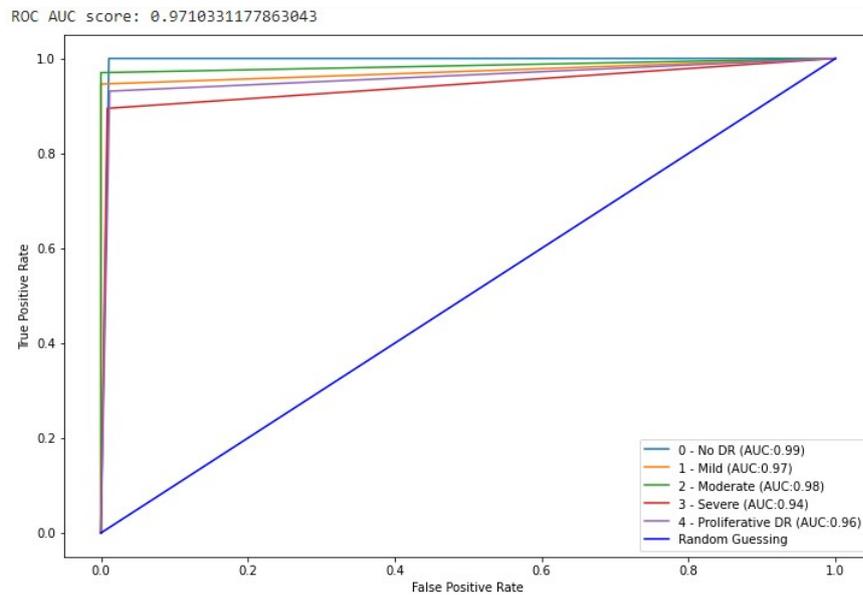
A validation set containing 365 photographic background images was used to evaluate the model. The model is evaluated based on the weighted average of the macro mean, precision, recall, and f1 scores to understand model performance using the researched single label classification method. Macro average and weighted average assessment of precision, recall and f1 score Five classes. The macro means are 0.94, 0.95, 0.94 and the weighted averages of 0.98, 0.98 and 0.98 of the precision, recall and f1 scores are recorded, respectively. Our model shows the best precision, recall and f1 scores of No DR, which are 0.99, 1.00, and 0.99, respectively. The assessment of the macro-mean and weighted

mean of the precision, recall and f1 score by the diabetic retinopathy classification system is presented in Table3.

**Table 4** Diabetic Retinopathy Classification system evaluation of Macro Average and Weighted Average for precision, recall, and f1-Score evaluated over 365 sample images of validation data

Classes	Precision	Recall	F1-support
No DR	0.99	1.00	0.99
Mild DR	1.00	0.95	0.97
Moderate DR	1.00	0.97	0.98
Severe DR	0.85	0.89	0.87
Proliferative DR	0.87	0.93	0.90
MacroAverage	0.94	0.98	0.95
Weighted Average	0.98	0.94	0.98

The Receiver Operating Characteristic (ROC) curve is a graph showing the performance of the classification model under all classification thresholds. The curve plots the rate of true positives versus the rate of false positives. the figure 11 illustrates the detailed results of the ROC graph of the classification model



**Fig. 10** The ROC graph of the classification model

## 4.2 Confusion Matrix

The confusion matrix describes the performance of the classification model on the validation set by comparing the actual label with the predicted label. The matrix confusion of our model is evaluated as a one-label classification method for five categories, as shown in Table 3. Each element of the confusion matrix shows the comparison of each image between the actual label and the label predicted. Configure verification. Our model shows the best DR-free results by making correct predictions on 180 images out of 180 images. Although the correct prediction images for mild DR, moderate DR, severe DR, and proliferative DR are 35, 97, 17, and 27 images out of 37, 100, 19, and 29, respectively. Table 4 illustrates the detailed results of the confusion matrix.

**Table 5** Confusion Matrix: The diagonal elements which represent the number of points for which predicted label matches true label, while non-diagonal elements are those that are wrongly classified by the classifier.

True Label / Predicted Label	No DR	Mild DR	Moderate DR	Severe DR	Proliferative DR
No DR	180	0	0	0	0
Mild DR	2	35	0	0	0
Moderate DR	0	0	97	1	2
Severe DR	0	0	0	17	2
Proliferative DR	0	0	2	2	27

## 5 Conclusion

By early detection and treatment of diabetic retinopathy, severe vision loss in diabetic patients can be prevented. Deep learning is one of the most advanced technologies for solving classification problems and provides better accuracy. The efficient convolutional neural network architecture used to detect and classify fundus images will help ophthalmologists further eradicate vision loss caused by diabetic retinopathy. In this article, we propose an EfficientNetB3 model for the early detection of the five severities of diabetic retinopathy. We have made several modifications to the EfficientNetB3 pre-trained network and used pre-processing to improve network performance. Our network was trained on APTOS 2019 dataset, which outperformed other state-of-the-art networks in early-stage detection. The accuracy of the proposed model is 98.26

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